# AUTOMATED DIAGNOSTIC APPROACHES FOR DETECTION AND CLASSIFICATION OF LUNG DISEASES FROM CT AND X-RAY IMAGES USING DEEP LEARNING MODELS

**A SYNOPSIS**

*Submitted by*

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## 1. INTRODUCTION

Rapid socio-economic development, urbanization, and changing lifestyles in developing countries like India lead to a rising burden of Non-Communicable Diseases (NCDs), notably Chronic Obstructive Pulmonary Disease (COPD). India's COPD mortality is significant, contributing to about 556,000 deaths annually, amidst a global toll of 2.74 million. Lung diseases, including COPD, rank third in global mortality, with over 3.23 million deaths in 2019. In India, lung disease mortality stands at 421.01 deaths per lakh, making it the leading cause of death nationally. These statistics underscore the urgent need for preventive and management strategies [1-3].

The lungs are sponge-like organs crucial for the respiratory system, characterized by low-density air spaces visible on CT images (about 1000 HU). They house pulmonary vessels and bronchi and are divided into lobes: the left lung has two lobes (upper and lower), separated by an oblique fissure, while the right lung has three lobes (upper, middle, and lower), separated by oblique and horizontal fissures. The thoracic cavity, containing the heart and lungs, is lined by pleural membranes, which also cover the lung surfaces [4]. Expansion of the thoracic cavity increases lung volume, leading to inhalation, where air flows into the lungs due to changes in air pressure.

Lung diseases are categorized by their impact on the airways, air sacs, interstitium, blood vessels, pleura, and chest wall. They disrupt breathing, affecting the airways (e.g., asthma, bronchiectasis, COPD [5]), lung tissue (leading to interstitial inflammation or scarring), and the circulation system. Interstitial inflammation causes alveolar stiffness, limiting oxygen delivery and carbon dioxide removal.Pneumonia is a lung infection characterized by alveoli inflammation, often caused by bacteria, viruses, fungi, or other microbes. It primarily affects the elderly, young children, and immunocompromised individuals [6]. Diagnostic methods include physical examinations, chest x-rays, CT scans, ultrasounds, and needle biopsies. Serious complications can arise, such as respiratory failure, infection spread, lung fluid accumulation, abscesses, and sepsis, which can be fatal. Prompt

medical attention is crucial for symptomatic patients. Identifying the causative agent through microbiological testing is essential for appropriate treatment.Tuberculosis (TB) is a major infectious disease affecting the lungs, with significant global impact. In 2015, it caused 1.8 million deaths and 10.4 million illnesses, predominantly affecting young adults in developing countries [7]. TB bacteria, spread through the air in droplets when an infected person coughs or sneezes, primarily attack the lungs. Infection can progress in different ways. Diagnosing TB involves assessing symptoms and clinical examination, supported by tests such as chest X-rays, tuberculin skin tests, and sputum analysis. Chest X-rays can detect active TB and indicate past infections.COVID-19, caused by SARS-CoV-2, has spread globally since December 2019, affecting millions. Symptoms include fever, cough, sudden cardiac arrest, organ failure, fatigue, pneumonia-like respiratory infection, and loss of taste and smell. Rapid mutations complicate diagnosis, with all ages at risk via respiratory droplets from infected individuals [8].

Biopsies involve taking a tissue sample with a fine needle for microscopic examination to assess suspicious lung problems. Chest X-rays use low-dose radiation for quick imaging, while CT scans provide detailed, overlay-free images of body parts. MRI employs magnetic fields and radio waves to create detailed internal organ images. The radical change in the field of Information Technology and medical imaging promotes the production and storage of large number of medical images. These images provide the critical anatomical and functional details needed for the accurate diagnosis of diseases. The drastic expansion in these fields made way for the evolution of Computer aided diagnosis (CAD) systems [9]. CAD tools have given promising results in their utility as diagnostic tools. Computer science, image processing, pattern recognition and artificial intelligence domains are integrated to develop a CAD system.Deep learning techniques have revolutionized the field of medical image analysis by enabling automated feature extraction and pattern recognition from complex image datasets. This thesis aims to harness the power of deep learning to address the challenges associated with lung disease classification.

## 2. LITERATURE REVIEW

Nur-A-Alam *et al.* [10] proposed a COVID-19 detection method utilizing feature fusion and deep learning. Thefeatures extracted from chest X-ray images was combined using HOG and CNN for classification. The watershed segmentation method was employed to locate the major fracture zone in input X-ray images. This approach enhances accuracy in identifying

COVID-19 from X-ray scans.Goyal and Singh [11] proposed a COVID-19 detection method using ML and DL. The proposed framework involved features extraction, dataset gathering, ROI estimation, picture enhancement, and disease prediction. Soft computing methods like neural networks, KNN, ensemble classifiers, SVM, and DL were employed. For accurate diagnosis, recurrent neural networks with large short-term memory were suggested.Alotaib *et al.* [12]explored ML methods for COVID-19 severity prediction, including support vector machines, random forest regression, and three types of artificial neural networks. The proposed study demonstrated the efficacy of ML in early severity assessment using patient data, facilitating improved triage and treatment decisions. These approaches leverage medical history and test results to accurately predict severity and prognosis, crucial for optimizing patient care.Shamima Akter *et al.* [13] proposed a deep learning (DL) model for COVID-19 detection on chest X-ray images, achieving high prediction rates. Eleven CNN models were evaluated, with MobileNetV2 selected for further modification to enhance accuracy. Performance analysis via confusion matrix highlighted the model's efficacy.Rahman *et al.* [14] investigated image enhancement's impact on COVID-19 detection via chest X-rays. An original UNet model was contrasted with a preexisting one for lung segmentation, finding plain CXR images slightly outperform segmented lung images in classification. Despite this, segmented lung images exhibit higher network performance reliability.

Kevser Sahinbas and Ferhat Ozgur Catak [15] introduced a transfer learning-based CNN for COVID-19 detection using X-ray images. Utilizing five pre-trained CNN models, the simulation found VGG16 to outperform others, achieving 80% accuracy in automatic COVID-19 classification. This underscores the significance of medical imaging tools like X-rays and CT scans in promptly diagnosing COVID-19, with VGG16 showcasing promising potential in this domain.Ozcan [16] proposed a composite method for COVID-19 detection in X-ray images using deep features. The approach combines deep X-ray image properties, offering single-layer-based (SLB) and feature-fusion-based (FFB) variations. Four SLB and six FFB models were generated based on layer quantity and binary configuration. These models were employed for both binary and multiple class classification trials, showcasing the versatility of the proposed approach. Ahmet Saygıl [17] proposed a new approach for computer-aided detection of coronavirus (COVID-19) from CT and X-ray images using machine learning methods. In this study, chest X-ray and CT images were utilized to examine the function of ML and image processing in the quick and precise recognition of COVID19. The major goal of this work is to assist early coronavirus identification and diagnosis. Zohreh

Mousav *et al.* [18] introduced a method for COVID-19 detection using chest X-ray images based on an enhanced deep neural network. This study suggests a method for categorizing 2-4 groups into 7 different Scenarios, including COVID-19, bacterial, viral, and healthy classes, using chest X-ray images. A CNN- LSTM combination is used for the detection of COVID-19.Taban Majeed [19] introduced a CNN transfer learning method for rapid COVID-19 detection on X-ray images. The CNN TL approach provided a basic model for discriminating COVID-19. The proposed approach also employed class activation maps (CAMs) for qualitative evaluation, highlighting regions influencing CNN decisions.

## 3. OBJECTIVES

The following objectives and corresponding tasks are formulated to achieve the goal:

- To implement an effective modelfor COVID-19 detection from chest X-ray images.
- To develop an efficient deep transfer learning models for enhancing theperformance of lung disease classification and reduce the misclassification rate.
- To compare the performance of the proposed models on chest X-ray and CT image datasets.
- To implement an ensemble learning approach for lung disease classification

## 4. RESEARCH PROBLEM

Developing accurate deep learning models for lung disease classification faces numerous challenges. Limited availability of large, annotated datasets, especially for rare disorders, hinders robust classifier development. Current methodologies lack efficient parameter optimization techniques crucial for model performance. High computational costs restrict effective data utilization, hindering scalability. Additionally, interpretability issues impede trust in clinical settings. Lung disease classification from diverse CT image data, especially full slices, remains challenging for existing models, highlighting the need for advanced approaches like ensemble learning. To address these, research focuses on optimizing deep learning methods for lung disease classification, emphasizing data availability, model optimization, computational efficiency, interpretability, and suitability for diverse image characteristics, particularly enhancing performance for chest CT analysis through novel ensemble learning methodologies.

## 5. CONTRIBUTIONS

## Covid-19 Detection and Classification from Chest X-ray Images Using DCNN Approaches

The major goal of this work is to produce accurate classification results using openly accessible data and mixed transfer learning models. A CNN-based DL architecture that is suitable for the Covid-19 classification. In this work, COVID-19 image classification is carried out using the Modified VGG-16, VGG-19, and ResNet 50 models. Finally, the performance parameters of the three models are examined. The block diagram for the suggested approach is illustrated in Figure 5.1.

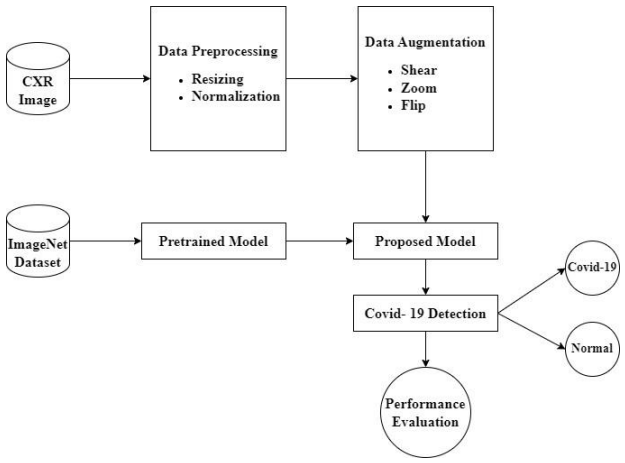



**Fig. 5.1.** Block Diagram of Proposed Covid-19 Detection Model

**Convolutional Neural Network:**

CNNs are key for image analysis, leveraging insights from the brain's visual cortex [20]. With prowess in image and video analysis, especially with datasets like ImageNet, CNNs comprise convolutional, pooling, and fully connected layers. Convolutional layers extract features, pooling layers reduce computational load, and fully connected layers classify data. The final layer, employing Softmax regression, yields class probabilities. The equation for generating class probabilities using Softmax function is expressed in Equation 1.

$$P = \frac{e^{Z_i}}{\sum_{j=1}^{k} e^{z_j}} \qquad (1)$$

**Transfer Learning:**

Transfer learning involves repurposing pre-trained models from one task to jumpstart learning on another related task [21]. It harnesses knowledge from the original task to boost efficiency and performance on the new task, crucial when data is scarce. Leveraging models

trained on vast datasets like ImageNet, transfer learning empowers the application of advanced features to specific problems, slashing training time and computational requirements while improving accuracy.

**Modified VGG-16:**

The VGG-16 model, developed by the Visual Geometry Group at the University of Oxford, is renowned for its effectiveness and simplicity in image classification. With 16 layers, including 13 convolutional and 3 fully connected layers, it employs 3x3 convolutional filters to capture intricate image details. Despite its depth, VGG-16 maintains simplicity by stacking convolutional layers followed by max-pooling layers. It achieved notable accuracy on benchmarks like ImageNet, showcasing the power of deeper networks with uniform architecture in visual recognition tasks.The basic architecture of VGG-16 is shown in Figure 5.2.

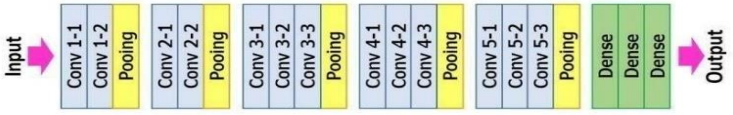



**Fig. 5.2.** Basic Architecture of VGG- 16

The modified VGG-16 design addresses overfitting by reducing network depth compared to the original architecture. It preserves VGG-16's essence by employing two successive small convolutional kernels for feature extraction instead of a single large one [22]. This strategy decreases parameters while maintaining perceptual effects and speeds up training. Each of the five blocks in the hidden layer consists of two convolutional layers and a pooling layer, with varying numbers of 3x3 convolutional kernels. Blocks 3 through 5 maintain 3x3 kernels but with 64, 128, and 64 kernels, respectively. Parameter reduction is achieved by decreasing kernel sizes. The model employs pooling to condense images, flattening for one-dimensional feature mappings, and three fully connected layers for classification into two classes.The proposed algorithm is explained below.

---

***Input:*** *CXR images*

***Output:*** *Efficient Covid-19 Detection and classification Model.*

---

***Begin:***

*Load and preprocess data:*

1. *Collect dataset:* $D = \{(X_i, y_i)$, *where* $X_i$ *is a CXR image and* $y_i \in \{0,1\}$ $y_i i \in \{0,1\}$ *(1: Normal, 0: Covid-19).*

2. *Preprocess:*

*Resize:* $X_i \rightarrow X_i' \in R^{224\times224}$
*Normalize:* $X_i \rightarrow \frac{X^F - \mu}{\sigma}$
*Data Augmentation:* $X_i' \rightarrow \{X_i''\}$*(Shear, Zoom, Flipp)*

*Define Base Models:*

1. *Load Models:* $M_{VGG16}, M_{VGG19}, M_{ResNet50}$
2. *Modified VGG-16 Architecture.*
   *Input:* $224 \times 224 \times 3$
   ***Block 1:*** *Conv2D (32, (3, 3))*
   *Conv2D (32, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*

   ***Block 2:*** *Conv2D (32, (3, 3))*
   *Conv2D (32, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*
   ***Block 3:*** *Conv2D (64, (3, 3))*
   *Conv2D (64, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*
   ***Block 4:*** *Conv2D (128, (3, 3))*
   *Conv2D (128, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*
   ***Block 5:*** *Conv2D (64, (3, 3))*
   *Conv2D (64, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*
   ***Global Max Pooling:*** *GlobalMaxPooling2D ()*
   ***Flatten:*** *Flatten ()*
   ***Fully Connected Layers:***
   *Dense (256, activation='relu')*
   *Dense (128, activation='relu')*
   *Dense (2, activation='softmax')*

*Model Compilation and Training:*

1. *Compile each model M:*
   *optimizer=Adam ()*
   *loss=binary_crossentropy*
   *metrics=[accuracy]*
2. *Train:* $M.fit(X_{train}, y_{train}, validation_data = (X_{val}, y_{val}))$

*Model Evaluation and Comparison:*

1. *Evaluate:*
   $metrics = M.evaluate(X_{test}, y_{test})$*, where metrics include accuracy, precision, recall.*

*Save the Model:*

***End***

**Dataset Description and Experimental Setup:**

The CXR image dataset was collected from Kaggle repository.It consists of two folders (test, train). Each subfolder consists of CXR images of Covid-19 and Normal cases.The models were created and trained on Google Collaboratory and the entire process was done in Python and TensorFlow.

**Results and Discussion:**

Table 5.1 displays the classification report of proposed models. The modified VGG-16 achieves 97.94% accuracy, surpassing ResNet 50 and VGG-19. Precision, measuring sample identification accuracy, is highest for the modified VGG-16 at 98.23%. Recall, indicating positive sample location effectiveness, is 95.58% for VGG-16, higher than VGG-19 and ResNet 50. VGG-19 and ResNet 50 attain 92.72% and 96.47% accuracy, 91.81% and 94.70% precision, and 90.90% and 94.99% recall, respectively.

**Table 5.1.** Classification Report of Proposed Covid- 19 Detection Models

| Model | Accuracy | Precision | Recall |
|---|---|---|---|
| VGG-19 | 92.72 % | 91.81 % | 90.90 % |
| ResNet 50 | 96.47 % | 94.70 % | 94.99 % |
| Modified VGG-16 | 97.94 % | 98.23 % | 95.58 % |

The accuracy plot and loss plot obtained for the proposed models are shown below.

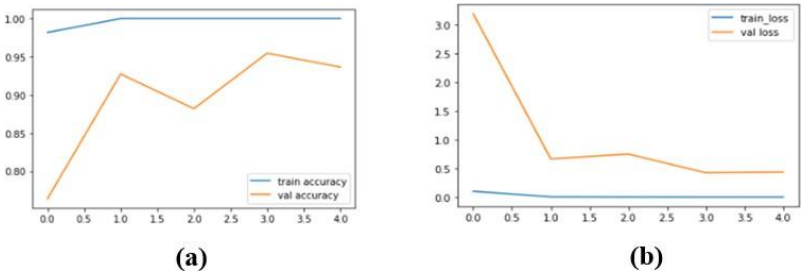



**Fig. 5.3.** (a) Accuracy Plot (b) Loss Plot of Modified VGG-16

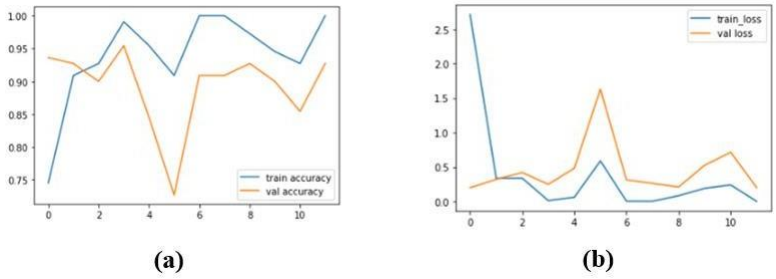
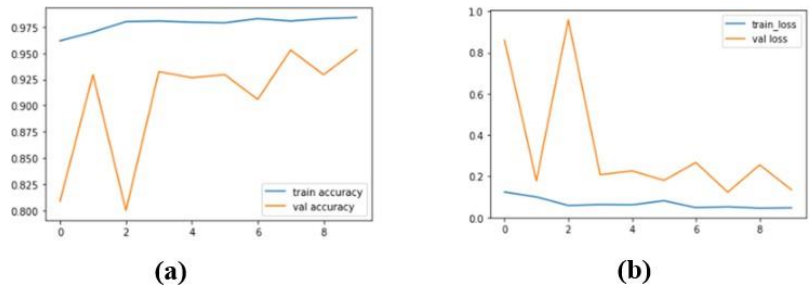



**Fig. 5.4.** (a) Accuracy Plot (b) Loss Plot of VGG-19




(a) (b)

**Fig. 5.5.** (a) Accuracy Plot (b) Loss Plot of ResNet 50

A modified VGG-16 framework is developed for COVID-19 detection from chest X-ray images, achieving 97.94% accuracy with reduced resources and training time compared to ResNet 50 and VGG-19. The model classifies images into two categories, outperforming existing models significantly.

**An effective lung disease classification Model Using Deep Transfer Learning Approach**

The proposed approach began with dataset collection, followed by preprocessing and augmentation. Pre-trained models on ImageNet were used to train on a CXR dataset for lung disease classification. The proposed method employs fine-tuned architectures, categorizing CXR images into five disease groups. Effectiveness is evaluated against existing approaches, as depicted in Figure 5.6.

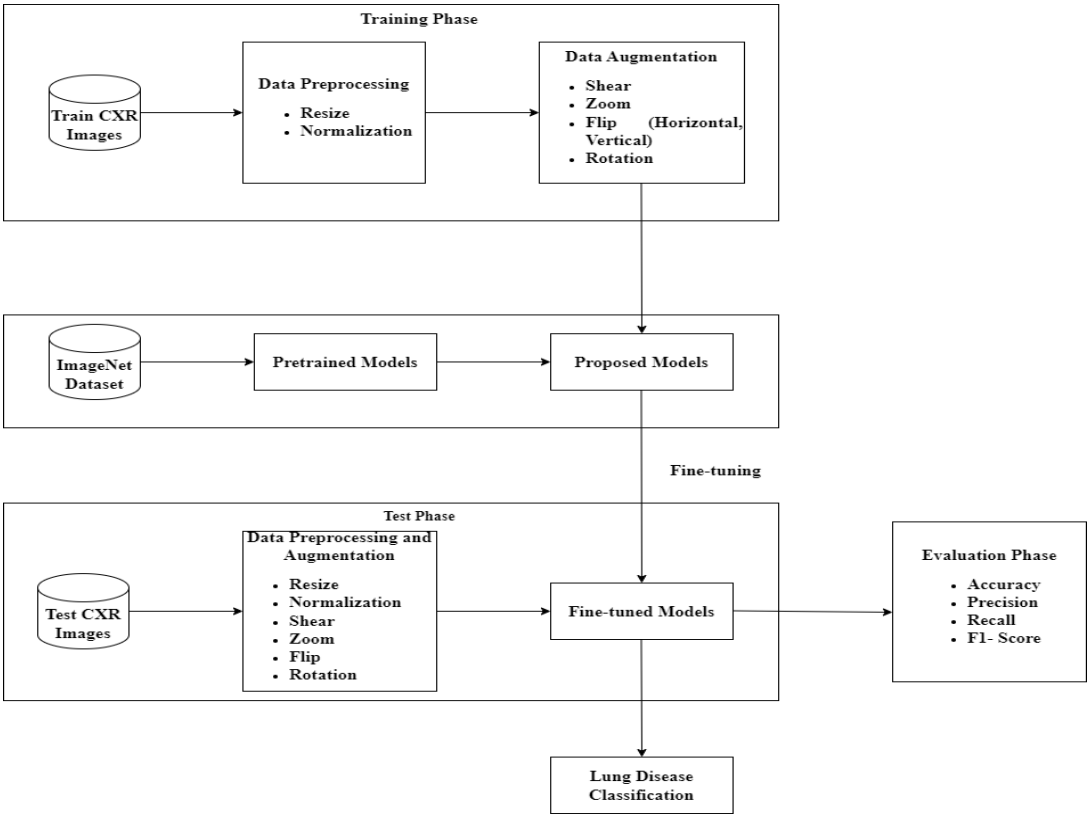



**Fig. 5.6.** Block Diagram of Proposed Lung Disease Classification Model

**Proposed Fine-tuned Architectures:**

Fine tuning is a deep learning technique where a pre-trained neural network's bottom layers are frozen to preserve generic features, while higher layers are retrained on a new dataset for a specific task. It enables efficient adaptation to new tasks with minimal data, but requires careful selection of model, dataset, and hyperparameters for optimal performance.

**Fine-tuned Modified VGG-16:**

The input imagesize was 224×224. There were five blocks in the hidden layer. The pooling layers diminished the size of theimage, while the flattened layer reduced the dimensionof the feature maps. Before fine-tuning, the modifiedVGG-16 model underwent 50 epochs of training. Finetuning was applied at the tenth layer onwards of the basemodel and provided a low learning rate. After completing the fine-tuning, the model was trained for fiftyepochs. The proposed algorithm for the fine-tuned Modified VGG-16 is described below.

---

***Input:***

- *A pretrained VGG-16*
- *A new dataset for fine-tuning*
- *Hyperparameters for fine-tuning (e.g.: learning rate, number of epochs etc.)*

***Output:****A fine-tuned Modified VGG-16 model for lung disease classification*

---

***Begin:***

*Load and preprocess data:*

3. *Collect dataset:* $D = \{(X_i, y_i)\}_{i=1}^{N}$ *where* $X_i$ *is a CXR images.*
4. *Preprocess:*
   *Resize:* $X_i \rightarrow X_i' \in R^{224\times224}$
   *Normalize:* $X_i \rightarrow \frac{X^F - \mu}{\sigma}$
   *Data Augmentation:* $X_i' \rightarrow \{X_i''\}$*(Shear, Zoom, Flipp (Horizontal, Vertical), Rotation).*

*Define Base Models:*

3. *Load VGG-16*
4. *Modified VGG-16 Architecture.*
   *Input:* $224 \times 224 \times 3$
   ***Block 1:*** *Conv2D (32, (3, 3))*
   *Conv2D (32, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*

   ***Block 2:*** *Conv2D (32, (3, 3))*
   *Conv2D (32, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*
   ***Block 3:*** *Conv2D (64, (3, 3))*
   *Conv2D (64, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*
   - ***Block 4:*** *Conv2D (128, (3, 3))*
   *Conv2D (128, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*
   ***Block 5:*** *Conv2D (64, (3, 3))*
   *Conv2D (64, (3, 3))*
   *MaxPooling2D (pool size= (2, 2))*
   ***Global Max Pooling:*** *GlobalMaxPooling2D ()*
   ***Flatten:*** *Flatten ()*
   ***Fully Connected Layers:***
   *Dense (256, activation='relu')*
   *Dense (128, activation='relu')*
   *Dense (5, activation='softmax')*
5. *Weight Initialization: Random initialization for new layers.*

*Fine tune the Model:*

1. *Compile Modified Model:*
   *model. Compile (loss='categorical_crossentropy', optimizer='Adam')*
2. *Fine-tuning from the 10th Layer Onwards:*
   *for* $l \geq 10$*, layer. trainable=True*
   *for* $l < 10$*, layer. trainable=False*
3. *Train the Model with Fine-tuning Hyperparameters:*
   *Base_learning_rate=* $\eta$
   *Lower_layer_learning_rate=* $\frac{y}{10}$

*Optimizer_higher_layers= Adam(learning_rate= η)*

*Optimizer_higher_layers= Adam(learning_rate= $\frac{\eta}{10}$)*

*history = model.fit (train_data,epochs=num_epochs, validation_data= (val_data, val_labels))*

4. *Update the Lower Layers:*

*Model Evaluation:*

2. *Evaluate:*
   *metrics=M.evaluate($X_{test}$ ,$y_{test}$), where metrics include accuracy, precision, recall and f1- score.*
3. *Adjust Hyperparameters:*
   *if test_accuracy < desired_accuracy: adjust hyperparameters and retrain*

*Save the Model*

***End***

**Fine- tuned VGG-19:**

A fixed-size RGB image was preprocessed by calculating mean RGB values per pixel. A 3x3 kernel with stride 1 and 2x2 pooling with stride 2 were employed. ReLU introduced non-linearity. VGG-19 had 3 fully connected layers, with the first 2 totaling 4096 units and the last using softmax. Fine-tuning began at the tenth layer with a low learning rate, following 20 epochs of initial training and 10 epochs post fine-tuning.

**Fine-tuned MobileNet V2:**

In the MobileNetV2 layout,the initial layer consists of a fully convolutional layerwith thirty-two filters, followed by nineteen bottlenecklayers, as shown in Figure 5.7. New design elements like squeeze and excitation blocks and inverted residuals enhances the architecture. Squeeze-and-excitation blocks capture channel-wise dependencies by lowering feature map dimensionality and determining channel-wise weights. The model undergoes 60 epochs of training, with fine-tuning applied after 85 layers, utilizing a low learning rate for 65 additional epochs.

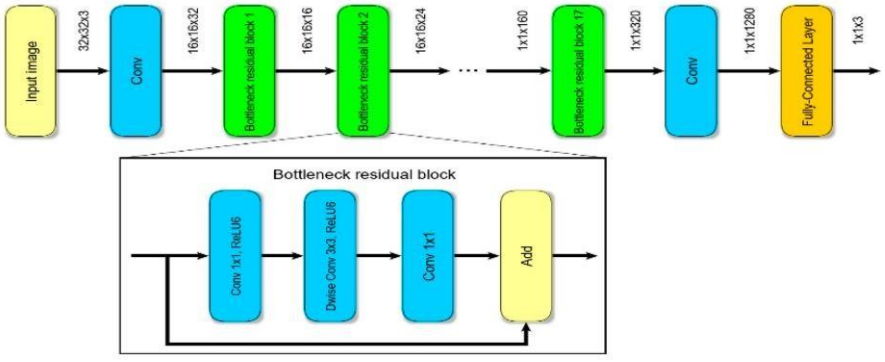


**Fig. 5.7.** Basic Architecture of MobileNet V2

**Dataset Description and Experimental Configuration:**

In order to create the new dataset, the two datasets werecombined with the sample dataset that was obtainedfrom Kaggle. In order to provide a robust computer, environment, this study utilized the Google Collaboratory andthe Microsoft Windows 10 operating systems.

**Result and Discussion:**

The accuracy plot and loss plot of the proposed fine-tuned models are visualized in below figures.

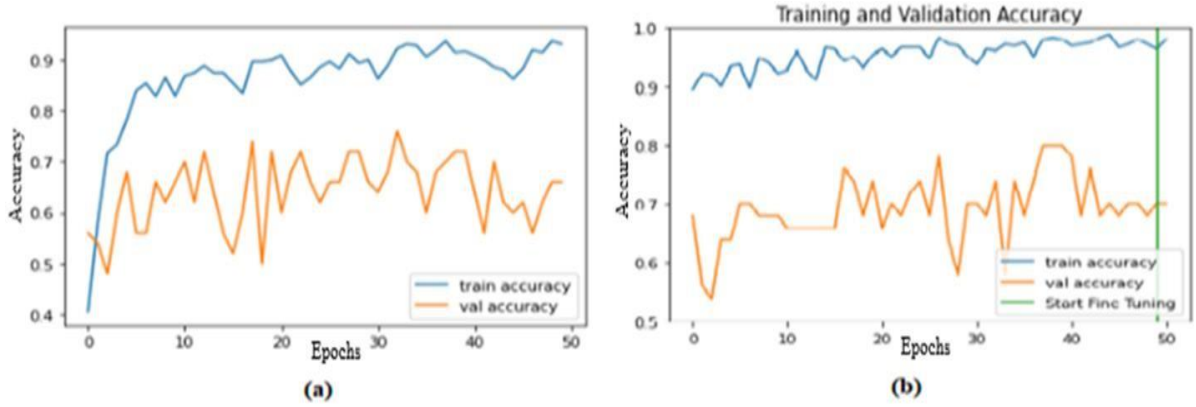



**Fig. 5.8.** Accuracy plot of fine-tuned Modified VGG-16 on CXR image dataset (a) before fine-tuning (b) after fine-tuning

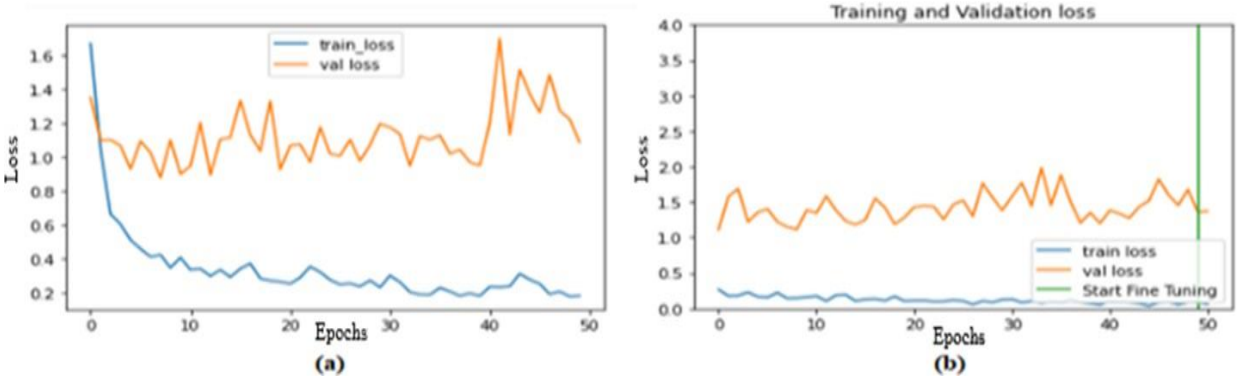



**Fig. 5.9.**Loss plot of fine-tuned Modified VGG-16 on CXR image dataset(a) before fine-tuning (b) after fine-tuning

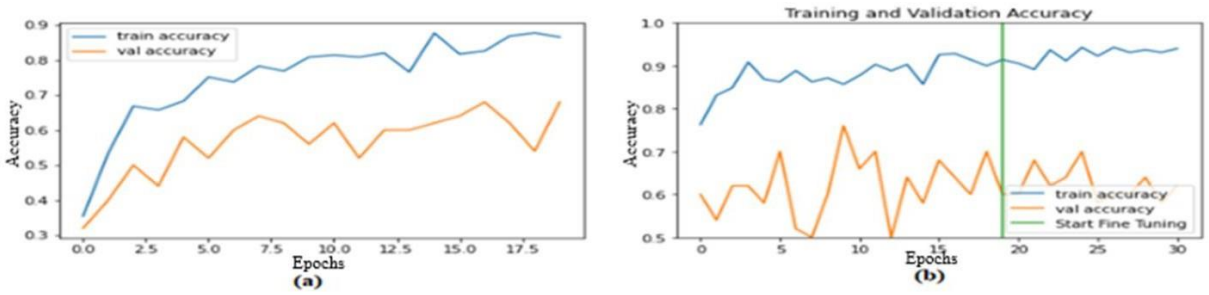



**Fig. 5.10.**Accuracy plot of fine-tuned VGG-19 on CXR image dataset (a) before fine-tuning (b) after fine-tuning

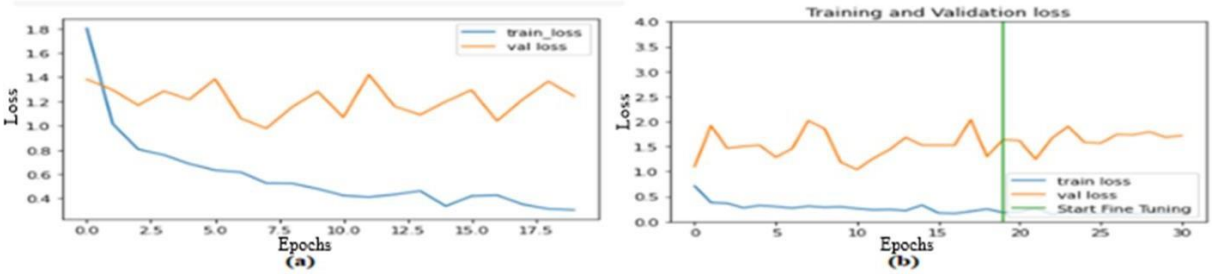



**Fig. 5.11.**Loss plot of fine-tuned VGG-19 on CXR image dataset(a) before fine-tuning (b) after fine-tuning

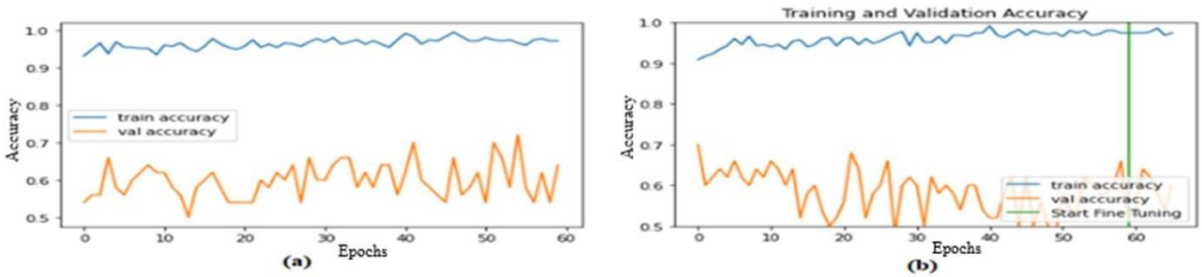



**Fig. 5.12.**Accuracy plot of fine-tuned MobileNet V2 on CXR image dataset (a) before fine-tuning (b) after fine-tuning

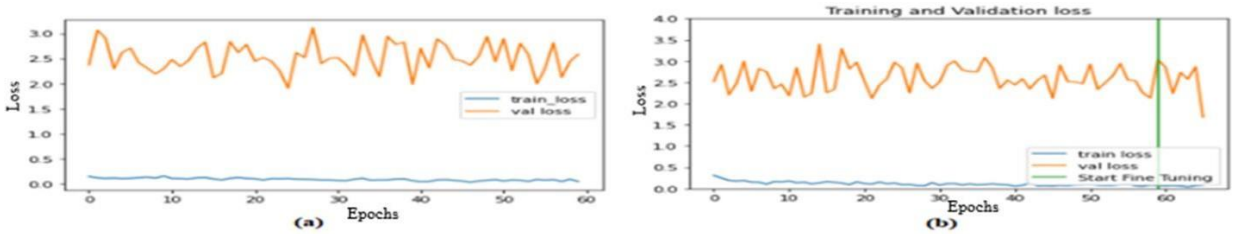



**Fig. 5.13.**Loss plot of fine-tuned MobileNet V2 on CXR image dataset(a) before fine-tuning (b) after fine-tuning

The classification report of the proposed fine-tuned models before and after fine-tuning is tabulated in Table 5.2.

**Table 5.2.** Classification Report of Proposed Fine-tuned Models

| Performance Metrics | Modified VGG-16 | | VGG-19 | | MobileNet V2 | |
|---|---|---|---|---|---|---|
| | Before Fine-tuning | After Fine-tuning | Before Fine-tuning | After Fine-tuning | Before Fine-tuning | After Fine-tuning |
| Accuracy | 93.14% | 98.00% | 86.57% | 94.00% | 97.14% | 97.43% |
| Precision | 93.42% | 98.57% | 88.85% | 91.14% | 97.71% | 97.74% |
| Recall | 91.71% | 98.28% | 88.28% | 92.28% | 97.14% | 97.42% |
| F1- Score | 94.85% | 98.57% | 86.57% | 92.28% | 94.42% | 97.56% |

The modified, fine-tuned VGG-16 modelperformed better than the other two models. The fine-tuned modified VGG-16 has got an accuracy of 98%.The suggested method can efficiently be employed forlung disease classification. The modified VGG-16 model has been evaluated on the CT image data and the comparison chart is shown in Figure 5.14.

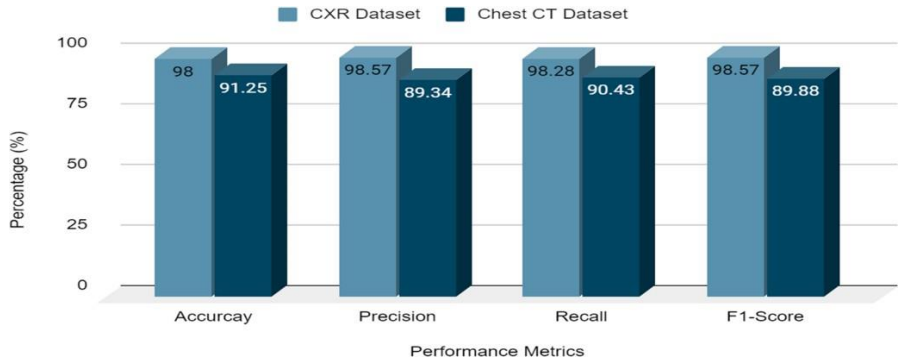



**Fig. 5.14.** Performance Comparison of Modified VGG-16 on CXR and CT Image Dataset

**Lung Disease Classification Using Bagging Ensemble Approach**

The proposed approach utilizes bagging ensemble technique to enhance classification model stability. It involves training three pre-trained models (Modified VGG-16, VGG-19, MobileNet V2) independently on CT image data, then averaging their probability scores to ensure equal weightage in the final prediction. Bagging iteratively selects and trains subsets of data for robustness. The Block diagram of the proposed methodology is shown in Figure 5.15.

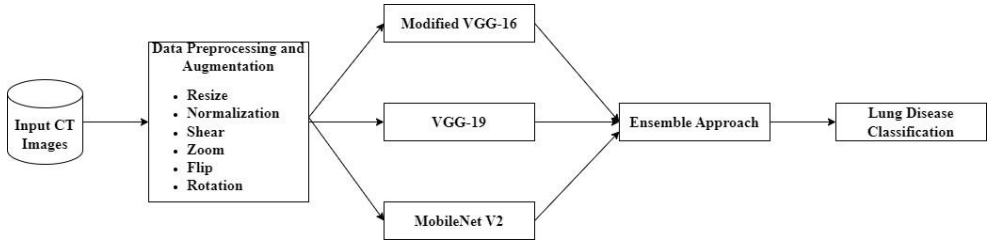



**Fig.5.15.** Block Diagram of the Proposed Ensemble Approach

Bagging, or Bootstrap Aggregating, enhances model robustness and predictive performance by training multiple base models separately on different training data subsets, created through bootstrap sampling. This involves randomly selecting subsets of the original training dataset with replacement. Three base models (Modified VGG-16, VGG-19, and MobileNet-V2) are trained independently using their bootstrap samples.Base models, trained on diverse subsets of CT image data, produce probability scores for lung disease classes. An ensemble model averages these predictions, ensuring equal contribution from each base model, promoting robust and generalized predictions. The proposed algorithm is explained below.

---

***Input:****Chest CT images*

***Output:****Efficient lung disease classification Model.*

---

***Begin***

*Load and Preprocess Data:*

- *Collect a dataset of lung CT images with corresponding labels*
- *Apply preprocessing steps such as resizing images to a fixed size (e.g., 224x224), normalization, and data augmentation*

*Define Base Models:*

- *Load Modified VGG16, VGG19, and MobileNetV2 models.*

*Model Compilation and Model Training:*

- *Compile each model with a suitable optimizer (Adam), loss function (categorical_crossentropy), and metrics (accuracy).*
- *Train each model separately on the training data and validate on the validation set.*

*Model Evaluation and Bagging Ensemble:*

- *Evaluate each trained model on the test set to get their individual performance metrics.*

*Combine Predictions Using Bagging:*

- *Use the trained models to make predictions on the test set.*

- *Combine predictions by averaging the probabilities from each model.*

*Evaluate Ensemble Model:*

- *Compare the ensemble predictions with true labels to compute accuracy and other performance metrics.*

***End***

**Dataset Description and Experimental Setup:**

The CT image dataset consists of five folders.Each folder consists of lung CT images of lung diseases.The proposed model has been trained and tested on Google Collaboratory platform using Python language. The proposed models underwent execution following the preparation of datasets and were developed and trained on Google Collaboratory using TensorFlow and Python. The Adam optimization technique was utilized for the purpose of categorization, with categorical cross-entropy working as the loss function and a selected batch size of 32.

**Result and Discussion**

The performance comparison of the proposed ensemble model is tabulated in Table 5.3.

**Table 5.3.** Performance comparison of Proposed Ensemble Method

| **Models** | **Accuracy** | **Precision** | **Recall** | **F1- Score** |
|---|---|---|---|---|
| VGG-19 | 88.53 % | 87.71 % | 87.99 % | 87.76 % |
| MobileNet V2 | 91.11 % | 90.25 % | 89.26 % | 89.96 % |
| Modified VGG-16 | 91.25 % | 89.34 % | 90.43 % | 89.88 % |
| Ensemble Approach | 97.99 % | 97.32 % | 97.58 % | 97.57 % |

The VGG-19 model achieved 88.53% accuracy, with precision, recall, and F1-Score around 87.7-88.0%, demonstrating good lung disease classification. MobileNetV2 performed better, with 91.11% accuracy and slightly lower precision, recall, and F1-Score values in the 89-90% range. The Modified VGG-16 model had 91.25% accuracy, with 89.34% precision and 90.43% recall. However, the ensemble approach significantly outperformed individual models, achieving 97.99% accuracy, 97.32% precision and recall, and a 97.57% F1 -Score. This highlights the ensemble method's superior potential for improving diagnostic accuracy in lung disease classification, offering a robust tool for the medical field.

## 6. CONCLUSION

The development and application of automated diagnosis approaches for the detection and classification of lung diseases from CT and X-ray images using deep learning models mark a

significant advancement in medical imaging and diagnostics. These approaches leverage the power of convolutional neural networks (CNNs) and other deep learning architectures to accurately identify and classify various lung conditions, including pneumonia, tuberculosis and covid-19.An effective lung diseaseclassification model based on fine-tuning mechanism isproposed in this research work. Three fine-tuned models wereemployed for the effective categorization of lung diseases from CXR images. Finally, abagging-based ensemble approach has been utilized for lung disease classification. The experimental results demonstrated superior performance in terms of accuracy, precision, recall and F1- score.

## 7. ORGANIZATION OF THESIS

The thesis is organized as follows: Chapter 1 provides a brief introduction of lung diseases. It clearly states the back- ground, research objectives and summary of contributions of the proposed research work. Chapter 2 provide a concise literature review that covers different models and techniques, offering descriptions of each model along with their respective strengths and weaknesses. The summary of the literature review is provided at the end with a suitable solution for lung disease classification.

Chapter 3 provides the detailed methodology of effective deep learning models for Covid- 19 detection from CXR images and the detailed discussion of the obtained results. Chapter 4 provides a detailed description of an intelligent framework for lung disease classification from CT images and CXR images incorporated with deep transfer learning and fine-tuning mechanism. Chapter 5 highlights the detailed methodology and obtained result discussion of an ensemble approach for lung disease classification from CT images. Chapter 6 a conclusion to the dissertation about future enhancements.

## 8. REFERENCES


1. World Health Organization. Chronic obstructive pulmonary disease.2021 [21 Jun 2021] Available from: (COPD)
2. Rabe KF, Hurd S, Anzueto A, Barnes PJ, Buist SA, Calverley P, et al.Global strategy for the diagnosis, management, and prevention ofchronic obstructive pulmonary disease. Am J Respir Crit Care Med.2007; 176:532–55.
3. GBD 2016 Causes of Death Collaborators. Global, regional, andnational age-sex specific mortality for 264 causes of death, 1980–2016:a systematic analysis for the Global Burden of Disease Study 2016.Lancet. 2017; 390:1151–210.
4. Leong, F., & Leong, A. (2010). Anatomy and Histology of the Human Lung. A Color Atlas of Comparative Pathology of Pulmonary Tuberculosis; Leong, FJ, Dartois, V., Dick, T., Eds, 31-51.
5. Ryu, J. H., & Scanlon, P. D. (2001, November). Obstructive lung diseases: COPD, asthma, and many imitators. In Mayo Clinic Proceedings (Vol. 76, No. 11, pp. 1144-1153). Elsevier.
6. Prayle, A., Atkinson, M., & Smyth, A. (2011). Pneumonia in the developed world. Paediatric respiratory reviews, 12(1), 60-69.
7. Hopewell, P. C., & Jasmer, R. M. (2004). Overview of clinical tuberculosis. Tuberculosis and the tubercle bacillus, 13-31.
8. Ciotti, M., Ciccozzi, M., Terrinoni, A., Jiang, W. C., Wang, C. B., & Bernardini, S. (2020). The COVID-19 pandemic. Critical reviews in clinical laboratory sciences, 57(6), 365-388.
9. Giger, M. L., & Suzuki, K. (2008). Computer-aided diagnosis. In Biomedical information technology (pp. 359-XXII). Academic Press.
10. Ahsan, M., Based, M. A., Haider, J., & Kowalski, M. (2021). COVID-19 detection from chest X-ray images using feature fusion and deep learning. Sensors, 21(4), 1480.
11. Goyal, S., & Singh, R. (2021). Detection and classification of lung diseases for pneumonia and Covid-19 using machine and deep learning techniques. Journal of Ambient Intelligence and Humanized Computing, 1-21.
12. Alotaibi, A., Shiblee, M., & Alshahrani, A. (2021). Prediction of severity of COVID-19-infected patients using machine learning techniques. Computers, 10(3), 31.
13. Akter, S., Shamrat, F. J. M., Chakraborty, S., Karim, A., & Azam, S. (2021). COVID-

19 detection using deep learning algorithms on chest X-ray images. Biology, 10(11), 1174.

14. Rahman, T., Khandakar, A., Qiblawi, Y., Tahir, A., Kiranyaz, S., Kashem, S. B. A., ... & Chowdhury, M. E. (2021). Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images. Computers in biology and medicine, 132, 104319.
15. Sahinbas, K., & Catak, F. O. (2021). Transfer learning-based convolutional neural network for COVID-19 detection with X-ray images. In Data Science for COVID-19 (pp. 451-466). Academic Press.
16. Ozcan, T. (2021). A new composite approach for COVID-19 detection in X-ray images using deep features. Applied Soft Computing, 111, 107669.
17. Saygılı, A. (2021). A new approach for computer-aided detection of coronavirus (COVID-19) from CT and X-ray images using machine learning methods. Applied Soft Computing, 105, 107323.
18. Mousavi, Z., Shahini, N., Sheykhivand, S., Mojtahedi, S., & Arshadi, A. (2022). COVID-19 detection using chest X-ray images based on a developed deep neural network. SLAS technology, 27(1), 63-75.
19. Majeed, T., Rashid, R., Ali, D., & Asaad, A. (2020). Covid-19 detection using cnn transfer learning from x-ray images. Medrxiv, 12, 2020.
20. O'shea, K., & Nash, R. (2015). An introduction to convolutional neural networks. arXiv preprint arXiv:1511.08458.
21. Torrey, L., & Shavlik, J. (2010). Transfer learning. In Handbook of research on machine learning applications and trends: algorithms, methods, and techniques (pp. 242-264). IGI global.
22. Tammina, S. (2019). Transfer learning using vgg-16 with deep convolutional neural network for classifying images. International Journal of Scientific and Research Publications (IJSRP), 9(10), 143-150.

## List of Publications

1. Shimja, M., & Kartheeban, K. (2024), **"Empowering diagnosis: an astonishing deep transfer learning approach with fine tuning for precise lung disease classification from CXR images"**, Automatika, 65(1), pp.192-205. SCI: 1.9.
2. Shimja M and K. Kartheeban, (2023), **"Beyond the Norm: A Modified VGG-16 Model for COVID-19 Detection"**, International Journal of Advanced ComputerScience and Applications (IJACSA), 14(11), pp.388-395, Web of Science(Clarivate | JIF 0.9.
3. Shimja M., and K. Kartheeban. (2024)," **A comparative study of lung disease classification using fine-tuned CXR and chest CT images**", Automatika 65. (1),pp.312-322. SCI:1.9.
4. Shimja M., and K. Kartheeban, (2021), **"Exploration of Prominence in clinical practices For Assessing Covid-19 Intricacies-Ultrasound interventional** International Conference on Advances in Computational Science and Engineering – AIP Conference Proceedings. Scopus.
5. Shimja M., and K. Kartheeban (2022), **"Machine Learning Methods to Detect Pneumonia of Lungs in Corona: A Survey"**, International Journal of Advance andInnovative Research, 9(1), 406-412
6. Shimja M., and K. Kartheeban (2023)," **Enhanced Covid-19 Detection Using CNN and Darknet: Advancing CT scan and Chest X-Ray Analysis**", Internationalconference on Intelligent Computing, Advanced Communication and Materials (IC 2ACM-23). Published / Not Indexed.
7. Shimja M., and K. Kartheeban (2024), **"Precise Lung Disease Classification Through Bagging Ensemble Method"**, International Conference on Circuit Powerand Computing Technologies. Accepted, Scopus Indexed.